CHANGE DETECTION FOR UPDATES OF VECTOR DATABASE THROUGH REGION-BASED CLASSIFICATION OF VHR SATELLITE DATA

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ABSTRACT:

Until now, interpretation of aerial photographs is a standard tool for monitoring land cover change where fine spatial resolutions are required and this task is expensive and time-consuming. Though, from a spaceborne perspective, the VHR satellite data are, since 1999, capable to meet the mapping and monitoring needs of municipal and regional planning agencies. Indeed, these data from the sensors Ikonos, QuickBird, OrbView-3, and in near future, the Pléiades-HR French sensors, have spatial resolution lower than 5 m in multispectral mode and lower than 1 m in panchromatic mode. These new sources of data combine the advantages of satellite data (synoptic view, digital format suitable for computer processing, quantitative land surface information at large spatial coverage and at frequent temporal intervals …) with the very high spatial resolution.

In spite of these advantages, the use of VHR satellite data involves some problems in traditional per-pixel classification often used in change detection techniques. There are still two occurring classification problems that can strongly deteriorate the result of a per-pixel classification of the VHR satellite data: spectral variability and poor spectral resolution. A solution to overcome these problems is the region-based classification that can be integrated in the common change detection techniques. The segmentation, before classification, produces regions which are more homogeneous in themselves than with nearby regions and represent discrete objects or areas in the image. Each image region then becomes a unit analysis and makes it possible to avoid much of the structural clutter. Image segmentation provides a logical transition from the units of pixels to larger units in maps more relevant to detect the changes in these.

In this context, this research project suggests to use region based classification of VHR satellite data in the change detection processe for updates of vector database.

1. INTRODUCTION

Up-to-date knowledge of **land cover** is an important tool for the various planning authorities with responsibilities for the management of territory (Marçal et al., 2005). The geospatial objects are changing over time and the land cover information (vector geospatial database) has to be up-date periodically. In general, change detection in a vector geospatial database involves the application of multi-temporal datasets to quantitatively analyse the changes. Because of the advantages of repetitive data acquisition, satellite remotely sensed data, such as Satellite Pour l'Observation de la Terre (SPOT), Thematic Mapper (TM), and Advanced Very High Resolution Radiometer (AVHRR), have become major data sources from local to global scales for different change detection applications during the past decades (Lu et al., 2003). However, planners and land managers require VHR data to address land cover problems at higher order thematic levels where spatial resolutions of 5 m or lower are required (Rogan and Chen, 2004).

The vector geospatial databases at a local scale in Belgium (e.g. National Geographic Institute 1/10000 topographic maps) were carried out by digital cartographic production process based on aerial photographs, and the update of these databases is now at the agenda.

Until now, interpretation of **aerial photographs** is a standard tool for monitoring land cover change where fine spatial resolutions are required (Loveland et al., 2002, Weis et al., 2005) and this task is expensive and time-consuming.

Though, from a spaceborne perspective, the **VHR satellite data** are, since 1999, capable to meet the mapping and monitoring needs of municipal and regional planning agencies (Treitz P., J. Rogan, 2004). Indeed, these data from the sensors Ikonos, QuickBird, OrbView-3, and in near future, the Pléiades-HR French sensors, have spatial resolution lower than 5 m in multispectral mode and lower than 1 m in panchromatic mode.
These new sources of data combine the advantages of satellite data (synoptic view, digital format suitable for computer processing, quantitative land surface information at large spatial coverage and at frequent temporal intervals …) with the very high spatial resolution (Prenzel, 2004).

In spite of these advantages, the use of VHR satellite data involves some **problems in traditional per-pixel classification** and the land cover classification is often used in change detection techniques.

The change detection techniques can be divided in two main types according to the data used to detect the changes: the **image-database** change detection and the **image-image** change detection.

In the first type the interpreted image is directly compared with the vector geospatial database.

Knudsen and Olsen (2003) detected the changes between a vector geospatial database and scanned aerial photographs, focusing on 'building' object class. They spectrally classified the scanned aerial photographs and overlaid the classification with the vector database in order to detect the new building.

Walter (2004) used a region-based classification for change detection. In this method, the objects, coming from the vector geospatial database that must be update, are spectrally classified and compared with the original database to detect the changes. This method is effective if a major change occurs in the original regions. Indeed, a change in the landscape can only be detected if it affects a large part of an object because the object-based classification uses the existing object geometry. If, for example, a building is built in a large forest area, this method fails to detect this new building.

In the second change detection type, Dai and Khorram (1999) characterize the **image-image change detection techniques** by their functionalities and the data transformation procedures. They define two broad categories:

- The techniques where only <u>changes and non-changes</u> are detected and no categorical change information can be directly provided (for example, image differencing, image rationing and image regression); and
- The techniques where complete <u>categorical changes</u> are extracted (for example, post-classification comparison and direct multidate classification).

In the first category, **changed and non-changed areas** are separated by a preset threshold when comparing the spectral reflectance values of multitemporal satellite images (Dai and Khorram, 1999). Then, the amount of change is a function of the preset threshold, determined by experiments in the tails of the histogram representing change information (Lu et al., 2003), that constitute a critical step of the change/no-change detection techniques. Moreover, these techniques involve often radiometric calibration between dates.

The simple detection of change is rarely sufficient in itself: information is generally required on the initial and final land cover types – the 'from-to' analysis where complete **categorical changes** are extracted (Fuller et al., 2003). The major advantage of the second category is the capability of providing a matrix of change information (transition detection matrix) and reducing external impact from atmospheric and environmental differences between the multi-temporal images (Lu et al., 2003). Post-classification (delta classification) comparison is a common approach used for change detection (Lu et al., 2003). The principal advantage of delta classification lies in the fact that the two dates of imagery are separately classified, thereby minimizing the problem of radiometric calibration between dates (Coppin et al., 2004). However, the accuracy of the post-classification comparison is totally dependent on the accuracy of the initial classifications. The final accuracy very closely resembles that resulting from the multiplication of the accuracies of each individual classification (Petit and Lambin, 2001, Coppin et al., 2004).

In practice, an analyst often selects several methods to implement change detection in a study area, then compare and identify the best results through accuracy assessment (Lu et al., 2003) but among all 'from-to' change detection techniques, a supervised digital classification is used and this type of classification is generally applied on a per-pixel basis.

In this framework, there are still two occurring **classification problems** that can strongly deteriorate the result of a per-pixel classification of the VHR satellite data (Irons et al., 1985, Smith and Fuller, 2001, De Wit and Clevers, 2004): spectral variability and poor spectral resolution.

The **spectral variability** is explained by the fact that with the spatial resolution refinement, the internal variability within homogenous land cover units increases (Cushnie, 1987, Woodcock and Stralher, 1987, Aplin et al., 1997, 1999, Carleer et al., 2005). The increased variability decreases the statistical separability of land cover classes in the spectral data space and this decreased separability tends to reduce per-pixel classification accuracies and the resulting per-pixel classification will have a speckled appearance (salt-and-pepper effect) (Smith and Fuller, 2001). The increased variability is attributed to the imaging of diverse class components by higher resolution sensors, whereas at coarser resolutions, sensors integrated the reflected spectral radiance of the various components and classes appeared more homogeneous (Irons et al., 1985). For example, the sunlit and shady sides of the same tree have vastly different spectral responses, even though they belong to the same class (Thomas et al., 2003).

Besides the problem of increased variability, the VHR data have a relatively **poor spectral resolution**. Generally, there is a trade-off between the spatial resolution and the spectral resolution (Alpin et al., 1997, Key et al., 2001).

While spatial resolution of the sensors is fine, spectral capabilities are generally limited compared to those of sensors currently in use such as Landsat Thematic Mapper (TM) (Aplin et al., 1997). This poor spectral resolution of the VHR satellite data can lead to problems in land cover interpretation (Herold et al., 2003). For example, the materials found in the urban environment include concrete, asphalt, metal, plastic, glass, shingles, water, grass, trees, shrubs, soil, … to list just a few, and many of these materials are spectrally similar, and this leads to problems in automated or semiautomated image classification of these areas if the spectral resolution is to poor (Shackelford et al., 2003). The VHR satellite data typically contain only four spectral bands.

Various **solutions** were developed to overcome these problems. For example, one possibility is proposed by Cushnie (1987) and Marceau et al. (1990) and consists of applying mathematical transformation to the original data to **remove the excess spectral detail** which is considered as noise (Cushnie, 1987). Some transformations are applied to the whole feature space (Principal Component Analysis …), while others are applied to individual bands through the process of spatial linear filtering. (e.g. mean-filter). This solution represents a reductionist approach, in the sense that they attempt to solve the problem of higher spectral confusion by eliminating part of the information that is present in the images.

A second possibility is to take advantage of the consequences of the increased resolution and to consider the internal spectral variance of classes as a valuable source of spatial information that can be used as an additional clue in characterizing and identifying land cover classes (Marceau et al., 1990, Shackelford et al., 2003). The **texture** is probably the most studied feature and is usually quantified using the statistics of image digital number (DN) within a window of interest, such as a 3- by 3- or 5- by 5-pixel window (Ferro and Warner, 2002), for example, the variance and the grey-level co-occurrence matrix (GLCM) of Haralick et al. (1973). But, a barrier to improving classification accuracies in image classification involving spatial patterns extracted from local neighborhoods (pixel windows) can be the misclassification that occurs at the boundaries of different classes (Gong, 1994). The textural features, calculated with a mobile window, create a between-class texture, which is often more distinctive than the within-class texture (Ferro and Warner, 2002).

Another solution is the **region-based classification** that can be integrated in the common 'from-to' change detection techniques. The segmentation, before classification, produces regions which are more homogeneous in themselves than with nearby regions and represent discrete objects or areas in the image. Each image region then becomes a unit analysis and makes it possible to avoid much of the structural clutter. Image segmentation provides a logical transition from the units of pixels to larger units in maps (Ryherd and Woodcock, 1996) more relevant to detect the changes in these.

Moreover, the image segmentation provides a good mean for the integration of land cover information from remotely sensed data in GIS, where the geospatial database are usually stored (Marçal et al., 2005).

In this context, the integration of the region-based classification in change detection techniques in order to detect the changes in local/regional geospatial vector database with VHR satellite data could be relevant.

2. STUDY ZONE AND DATA

The study area is situated in the southeast of Belgium, near the city of Arlon. The image data are panchromatic and XS QuickBird images acquired on 12 May 2004 with a spatial resolution of 0.6 m in the panchromatic band and 2.4 m in the multispectral bands. The study area covers 59 km² but for this study a 900mx900m study zone was used.

This study zone was extracted from the orgthorectified QuickBird image and from the TOP10V-GIS IGN vector database. The TOP10v-GIS database is the vector Belgian National Geographical Institute 1/10000 topographic map. This land use/cover database is constituted of 93 classes. Then, a generalization is essential.

With the satellite image and the vector database, a class transition reference was made. This reference allows to assess the change detection.

3. METHOD

The image – database change detection was chosen for this study in order to avoid radiometric correction, errors accumulation with the post-classification comparison and to use a priori knowledge from the vector database.

In order to directly integrate the data, the database can be used in the segmentation process and constrains this. Then the database is used as basis of the image segmentation. Each region of the database is segmented in order to detect the different objects that compose them. That ensures the integration and the matching at the same time.
These objects are classified and compared with the database classes in order to detect the changes. Another advantage of this method is to keep all database information and to do the generalization at different step of the process on the database and on the segmentation at the same time.

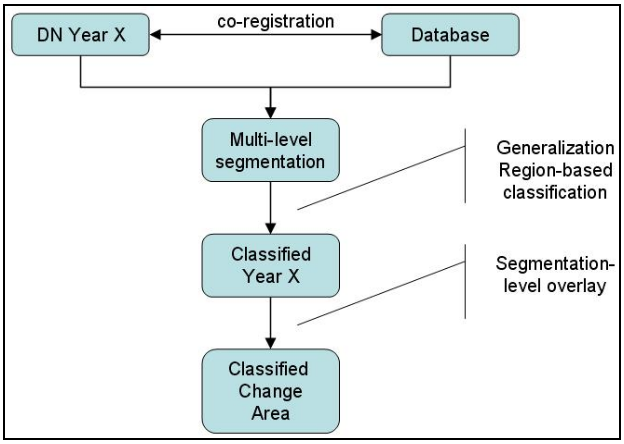

Figure 1. Used change detection method

3.1 Co-registration

Of the various requirements of preprocessing for change detection, spatial registration and radiometric calibration are the most important (Lu et al., 2003, Prenzel, 2004, Rogan and Chen, 2004). Due to the used method the radiometric calibration is useless but the importance of accurate spatial registration of multi-temporal imagery and databases is obvious because largely spurious results of change detection will be produced if there is misregistration (Lu et al., 2003, Coppin et al., 2004). The QuickBird image was orthorectified according to the database and with a 10x10 m DTM available on the study zone.
The geometric registration error between the images and the IGN database is expressed in terms of an acceptable total root mean square error (RMSE), which represents a measure of deviation of corrected GCP coordinate values from the original references GCPs used to develop the correction model. The lower RMSE achieved in this process is necessary to reduce the possibility of any false change detections due to misregistration of the co-registered image and database. The table x presents the RMSE for the panchromatic and XS QuickBird images.

	Nb GCP	X RMSE	Y RMSE
Panchromatic	48	0,98	1,54
XS	48	0,25	0,39

Table 2. RMSE for the QuickBird panchromatic and XS images (expressed in pixel of the orthorectified image)

3.2 Segmentation

The **segmentation** technique used in this project will be a bottom up "Region Growing" technique implemented in the eCognition software. The procedure starts at each point in the image with one-pixel regions and in numerous subsequent steps, smaller image regions are merged into bigger ones until a certain heterogeneity value (scale parameter) is reached. The larger the scale parameter, the larger the image regions. This segmentation technique is not very sensitive to the texture (Carleer et al., 2005), very present in VHR data, and makes it possible to segment the image on several levels (**multi-level**). Each level is defined by a growing scale parameter value and is made up of the merger of the lower level regions. It was shown that in fact a single optimal scale could not accurately represent all classes in a complex scene, due to the contrasting sizes, shapes, and internal variation of the patches for different land-cover classes (Raptis et al., 2003, Ju et al, 2005). The multi-level segmentation allows to identify different objects in different segmentation level. Like said above, the database is used as basis of the image segmentation and each region of the database is segmented in order to detect the different objects that compose them.

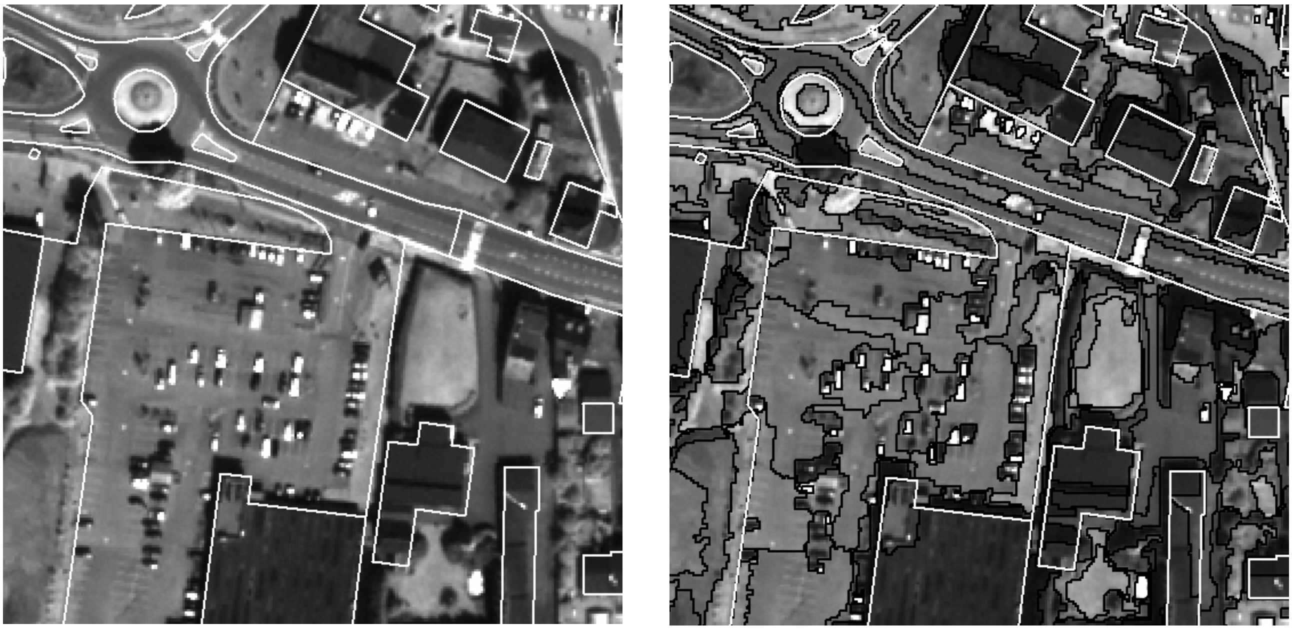

Figure 3.Extract of the orthorectified panchromatic QuickBird image,
(A) segmentation level 1 based on the vector database and (B) segmentation level 2.

3.3 Classification and Change Detection

The legend used in this study is presented in the table x. It is divided in to two levels. The first level is the classes coming from the database and the second level classes are the transition detected in this study. The shadow remains a recurrent problem in very high spatial resolution remote sensing and is considered like no change in this study.

Level 1		Level 2	
Barren surfaces	1	Barren surfaces	11
		Shadow	11
		Vegetation	14
Building	2	Building	22
		Shadow	22
		Vegetation	24
Road	3	Road	33
		Shadow	33
		Vegetation	34
Vegetation	4	Vegetation	44
		Shadow	44
		Bare soil	44
		ALERT	4x
Water	5	Water	55

Table 4. Hierarchical classification legend

The first segmentation level was classified according to the database classes in order to recover the database information. At this step a semantic generalization was carried out (see Table 3). For example, the 22 vegetation classes of the TOP10V-GIS database were gathered together in one vegetation class.

The second segmentation level was classified according to another legend in order to do the comparison with the first segmentation level to detect the changes. This second classification level was constrained by the first level classification according to the hierarchical legend. This constraint allows to directly identifying the changes (or transitions).

3.4 Change Detection Evaluation

Commonly, the change detection is assessed by different kind of matrixes completed by overlaying the change detection results with a reference. From the change/no change error matrix one can calculate how accurately change was distinguished from no change. But in the case of method that distinguish land-cover classes it is not meant for reporting the correctness of class assignment and therefore it does not report the frequency of “true no change, incorrect class” errors, nor does it report the frequency of “true change, incorrect class” errors. If done is also interested in the latter, then one needs the full transition error matrix (van Oort, 2007).

According to the legend, the entire transition matrix can not be completed. Only the class transition from- or to-vegetation (transition classes: 14, 24, 34 and 4x) are present. Then, the transition matrix is completed with these transition classes.
From these two matrixes, the change detection accuracy and the transition detection accuracy are calculated.

4. RESULTS

The results of the “from-to” change detection are presented in the transition and change/no change matrixes.

The change detection accuracy and the transition detection accuracy can be both calculated from the transition matrix.

The change detection accuracy = **92.2%**, and the transition detection accuracy = **90.5%**.

These results are very good and show that the changes were distinguished well from no changes, and that the classes are well classified. But the transition matrix highlights other interesting values.

The classification detects twice as much change than the reference but detects 70.5% of the true changes.

		REFERENCE									
		NO Change					Change				
CLASSIFICATION		11	22	33	44	55	14	24	34	4x	Total
NO Change	11	**214921**	2051	5682	2786	1	5679	0	121	1835	233076
	22	2888	**233710**	133	10400	0	0	63	0	404	247598
	33	303	0	**150969**	2881	0	0	0	3351	263	157767
	44	2205	472	5950	**1371159**	634	154	3	365	14943	1395885
	55	5	0	0	591	**2273**	157	0	0	0	3026
Change	14	31168	38	1935	867	2173	**18463**	0	0	485	55129
	24	153	10553	1	1046	0	0	**0**	0	23	11776
	34	120	0	22814	1142	0	0	0	**1988**	0	26064
	4x	523	783	2036	71882	0	4	0	67	**44384**	119679
Total		252286	247607	189520	1462754	5081	24457	66	5892	62337	2250000

Table 5. The transition detection matrix allows to assess the change detection method.

The fact that the classification detects twice as much change is easily explained. In the images there are a lot of occlusions of the roads, buildings and other surfaces by vegetation (trees) or shadows. Moreover, changes are detected in some regions like garden. The gardens are considered like vegetation but parts of them are not covered by vegetation. There are terraces, paths or car ways and all these parts are detected like changes compared as vegetation.

The 70.5% of change detection is explained in part by the classification errors but also by the class definition outlined above.

5. CONCLUSION

This study case presents encouraging results in the change detection process.

The Road, Building and Barren surfaces classes should be added in the second legend level in order to identify the new or modified roads and buildings and to complete the transition matrix. This kind of change, from- and to- Road, Building and Barren surfaces transitions represent 13.8% of changes occurred in this study zone.

The difficulty is to identify these classes. Some land cover types have very similar spectral characteristics. Some classes have a constant low reflectance over the whole spectral range with no or only minor distinct absorption features. For example, problems of misclassification occur between buildings and roads which are caused by spectral similarities between materials covering these surfaces and the influence of shadow. Then, the use of other information on top of spectral information for the classification of these classes is essential.

The segmentation allows to measure and use a number of features, on top of spectral features (Herold et al., 2003, Thomas et al., 2003). These features can be the surface, the perimeter, the compactness (area/perimeter²), the degree and kind of texture and the context (Johnsson, 1994). The segmentation is one of the only methods that ensure to measure the morphological features (surface, perimeter, shape…) (Segl and Kaufmann, 2001) which may be especially useful when very high spatial resolution data are available (Jensen and Cowen, 1999). Some studies like Carleer and Wolff, 2006 already show that the textural and morphological features are essential in the identification of the Road and Building classes
The use of additional features could allow to compensate for the poor spectral resolution of VHR satellite data (Guindon, 2000, Herold et al., 2002) and to increase the classification accuracy for spectrally heterogeneous classes (Lillesand and Kiefer, 1994). Some of these additional features are already used in per-pixel classification but with segmentation the spatial features are calculated on specific regions, without taking into account nearby regions like in the per pixel methods for which a mobile windows is used with an arbitrary neighborhood (Carleer et al., 2005).

The classification legend and parameters must be improved, solution must be found to overcome the class confusion and the occlusion problem. Also, the shadow remains a great problem in the interpretation of VHR satellite data even if some solutions based on shadow interpretation were investigated (Carleer and Wolff, 2006, Dare, 2005).

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